

FRAMEWORK FOR INTEGRATED MULTI-OBJECTIVE OPTIMIZATION OF PRODUCTION AND INDUSTRIAL BUILDING DESIGN

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Abstract

Integrated industrial building design, incorporating building and production planning, is challenging due to sequential processes and isolated use of discipline-specific tools. Integrated optimizations are seldomly performed and sufficient decision support is lacking at early design stage. This paper presents a parametric framework for semi-automated multi-objective optimization and decision support (PMOOD) for flexible and eco-efficient industrial building structures, integrating production layout planning. The evolutionary algorithm finds best performing design solutions in terms of life cycle costs, life cycle assessment, recycling potential and flexibility. We evaluated the framework in an interdisciplinary user study based on a pilot-project from a hygiene production facility.

Introduction

Improving the performance of industrial buildings at early design stage is crucial for a sustainable built environment, as these building types produce and consume a huge amount of energy, materials and costs for construction and operation (Heravi et al., 2015, San-José Lombera and Garrucho Apea, 2010). Industrial building design is a complicated task as interdisciplinary design teams try to counterbalance various conflicting parameters that are subject to different constraints. Manufacturing processes are frequently subject to change because of fast-advancing technologies and product individualization, presenting challenges to the rigid load-bearing structure of the building. It is vital to analyze and optimize the load-bearing structure and production systems in an integrated manner towards maximum flexibility in order to avoid premature rescheduling and demolitions. However, typically, structural design considerations enter the design process after architectural and production decisions have been made (Mueller, 2014, Bejjani et al., 2018). To improve the overall performance of industrial buildings it is necessary to seek a balance among conflicting objectives. Integrated optimization is rarely performed in current industrial building design due to sequential production and building design processes and a lack of data and model interoperability (Kampker et al., 2013, Ebade Esfahani et al., 2019).

Multi-objective optimization (MOO) models, searching for solutions that consider the trade-off between different

objectives, can enable automation of integrated designs and building performance optimization to find efficient designs and avoid time-consuming tasks in manual generation of alternatives (Manni and Nicolini, 2022). Commonly used optimization techniques in building design cannot always guarantee that the optimal solution is found. Nevertheless, better building performance can be achieved with these optimization algorithms than in common practice when no optimization is used (Machairas et al., 2014). Building performance simulation with multi-objective optimization algorithms have been widely used by researchers to explore new designs, which would not be accessible through traditional design approaches. Yet, either researchers use multi-objective optimization methods for production layout generation (Garcia-Hernandez et al., 2020, Aiello et al., 2013) or for structural building performance optimization (Brown et al., 2020, Brown and Mueller, 2016, Pan et al., 2019); a mutual consideration of production and structural design for integrated optimization has not been widely investigated. Furthermore, architects and engineers rarely consider flexibility when designing production facilities (Madson et al., 2020). Concluding, new integration and optimization methods focusing on the development of low-emission, cost-effective and flexible structural systems are needed to reduce the economic and environmental impacts of industrial buildings.

This paper presents ongoing research conducted within the research project BIMFlexi, which aims to develop a holistic digital platform for design and optimization of flexible industrial buildings for industry 4.0 (Reisinger et al., 2020). The presented research of this paper aims to bridge the research gap of an integrated design method for coherent optimization of production layouts and industrial building structures and presents an integrated parametric multi-objective optimization and decision support (PMOOD) framework for the design of sustainable and flexible industrial buildings, considering dynamic production layouts. The research builds up on our previous work, where a parametric method for automated generation and multi-objective optimization of production layouts (PLGO model) (Reisinger et al., 2022b) and a parametric optimization and decision support framework for automated structural analysis with parallel performance assessment of life cycle costs (LCC), life cycle assessment (LCA), recycling potential and flexibility of industrial building structures (POD model)

(Reisinger et al., 2022a) were developed. The mentioned POD model did not include an automated multi-objective optimization routine. This is a major limitation, as the designers have to manually explore the design space to find well performing designs. Manual design exploration is an ineffective and time-consuming process where only a smaller number of design alternatives can be tested (Touloupaki and Theodosiou, 2017). In this paper, an evolutionary multi-objective optimization algorithm is implemented in the POD model to automate the design exploration search. The POD model enhanced by the optimization algorithm results in the presented PMOOD model, which now automatically finds best-performing structural building solutions that are optimized with respect to the objectives of improved LCC, LCA, recycling potential, and flexibility performance. In addition, the PLGO model is integrated into the structural optimization process to enable coherent optimization of production layouts and industrial buildings. The objective of this study is to test the PMOOD framework and implemented optimization algorithm to determine whether it provides feasible and satisfactory industrial building design results. Using a test case from a hygiene production facility, a user study is conducted with architectural and civil engineering students to evaluate if the automated PMOOD model provides better results than working with the POD model. The evaluation of the PMOOD model and algorithm is the focus of the user study. The multi-objective optimization of production layouts within the PLGO model is not part of this study.

Literature review

Evolutionary algorithms are widely used in multi-objective optimization of building designs and can be applied to design problems such as façade design, orientation, thermal comfort, energy use, structural analysis and life cycle analysis (Machairas et al., 2014). Touloupaki and Theodosiou (2017) reviewed methodologies of performance-driven design optimization using parametric design, revealing that Rhino and Grasshopper are the software packages that currently dominate the field of computational performance-driven design. Future research should concentrate on making interfaces more user-friendly, and ensure that no coding skills are required. Further integration is needed to achieve seamless operation and interoperability without multiple software installation packages. Manni and Nicolini (2022) conducted a synthetic review on multi-objective optimization models to design climate-responsive buildings, revealing that most investigated models optimize energy performance and thermal comfort, less research focuses on minimizing LCC or LCA. Within the Grasshopper environment, existing plug-ins such as Opossum, Galapagos, Colibri, and Octopus were utilized in previous studies. Various researchers examine methods for parametric structural performance optimization with different purposes and goals. Gan et al. (2019) propose a parametric optimization approach using a genetic algorithm to optimize topology and element size for designing cost-optimal and low-

carbon high-rise reinforced concrete structures. Turrin et al. (2011) presented the multidisciplinary optimization tool ParaGen that combines parametric modeling, structural and energy performance simulation and a genetic algorithm, which is tested on a long span roof structure. Brown et al. (2020) present the parametric toolbox Design Space Exploration for multi-objective optimization, structural and energy simulations and design exploration demonstrated on a case study involving complex geometry. Yi et al. (2021) developed a parametric method to integrate the criteria of several performances into multi-objective optimization. On a test case of a truss system, the daylight and the structure strength are maximized and the system's weight, and the material cost minimized. Apellániz et al. (2021) present a parametric building design approach to optimize LCA and structural performance, using the One Click LCA plug-in for Grasshopper for environmental impact assessment, Karamba3D for structural analysis and Octopus for multi-objective optimization. An optimization approach to improve the flexibility of building structures by integrating the internal spatial requirements in the building has not yet been extensively studied. We have presented a parametric design framework for industrial buildings, integrating production requirements, and enabling structural performance assessment of LCA, LCC, recycling potential and flexibility (Reisinger et al., 2022a), however, the framework does not integrate automated design space exploration with multi-objective optimization. Several authors in production planning research use multi-objective evolutionary algorithms for automated generation and optimization of production layouts and processes (Garcia-Hernandez et al., 2020, Aiello et al., 2013), neglecting the integration of building constraints. A parametric method for automatically generating production layouts and for multi-objective optimization considering building criteria was presented by Reisinger et al. (2022b), however, the approach has not yet been integrated into a multi-objective optimization framework for automated generation of flexible building structures. Concluding, most of the reviewed workflows perform optimization at a single scale such as building or production without linking them. It is necessary to establish multi-objective optimization models operating at multiple scales, enabling to solve objective functions concerning different environments i.e., the production space and the building structure.

Methodology

This paper presents the enhancement of the previously developed POD model (Reisinger et al., 2022a) into the PMOOD model through integration of a multi-objective evolutionary algorithm for automated design generation, exploration and optimization. To enable the consideration of changing production layout scenarios in the structural design search, the PMOOD model is coupled to the PLGO model for automated generation and multi-objective optimization of production layouts (Reisinger et al., 2022b), resulting in the PMOOD framework. Both models were developed in the visual programming tool

Grasshopper for Rhino3D (McNeel, 2020), while the PMOOD model is supplemented with Karamba3D components for structural analysis (Preisinger, 2020). The integrated industrial building design process of the PMOOD framework is enabled by coupling the Grasshopper models of PLGO and PMOOD via excel-based programming. The PMOOD model aims to find best performing structural design variants with the objective to improve the LCC, LCA, recycling potential and flexibility performance. As these multiple objectives are conflicting, a Pareto-based approach was chosen to find trade-off solutions. The evolutionary algorithm for multi-objective optimization is written and implemented in the parametric PMOOD model within a C# component. Thereby, the following three different Pareto evolutionary algorithms have been implemented: SPEA2, SPEA2+SDE and CTAEA (Zitzler et al., 2001, Li et al., 2014, Li et al., 2019). The implementation of the algorithms in the parametric framework for automated industrial building design is novel and a customized user interface for the optimization in the parametric framework has been developed. The resulting PMOOD framework and the algorithm are tested on a pilot-project from a hygiene production facility in Austria. Within empirical research, the framework and the generated design results of the algorithm are evaluated in an experimental user study with interdisciplinary design teams involving 36 students from architecture and civil engineering from TU Wien. For the user study, the CTAEA was chosen as the optimization algorithm.

PMOOD framework

Framework for multi-objective optimization of production layouts and industrial building structures

The integrated industrial building design process is enabled by coupling the Grasshopper models of PLGO and PMOOD via excel programming as presented in

Figure 1. The PLGO and PMOOD model could be used as independent design and optimization tools. However, to achieve integration and to find highly flexible industrial building solutions that incorporate changing production processes, the models are coupled into an integrated design process. The computational models automatically generate production layout and building options, conduct automated performance assessment and objectives calculation and integrate an evolutionary multi-objective optimization approach. Building and production requirements and constraints such as property size, maximum building height or the desired production program serve as input to start the PLGO optimization process. Multiple production layout scenarios are generated and ranked by their performance by the PLGO algorithm. After production layout optimization, the users have to manually explore and select the preferred production layout scenarios provided by the PLGO model before integrating and investigating them in the building simulation. This manual interaction is intended as it allows the experts knowledge to be incorporated into the design process, rather than relying solely on the best-rated scenarios generated by the algorithm. To consider the selected layout scenarios and their geometric and load requirements in the structural optimization process, the data exchange between the PLGO model and the PMOOD model is automated and enabled through excel data format. The input to start the PMOOD model optimization are the user and property requirements from the input mask and the integrated production layout scenarios. After the automated generation and multi-objective optimization of the building options, the users have the possibility to go through the ranked options, set objective weightings and select the preferred design based on performance and visualization in Rhino 3D. The focus of this paper is on the presentation and evaluation of the PMOOD model and algorithm. The framework,

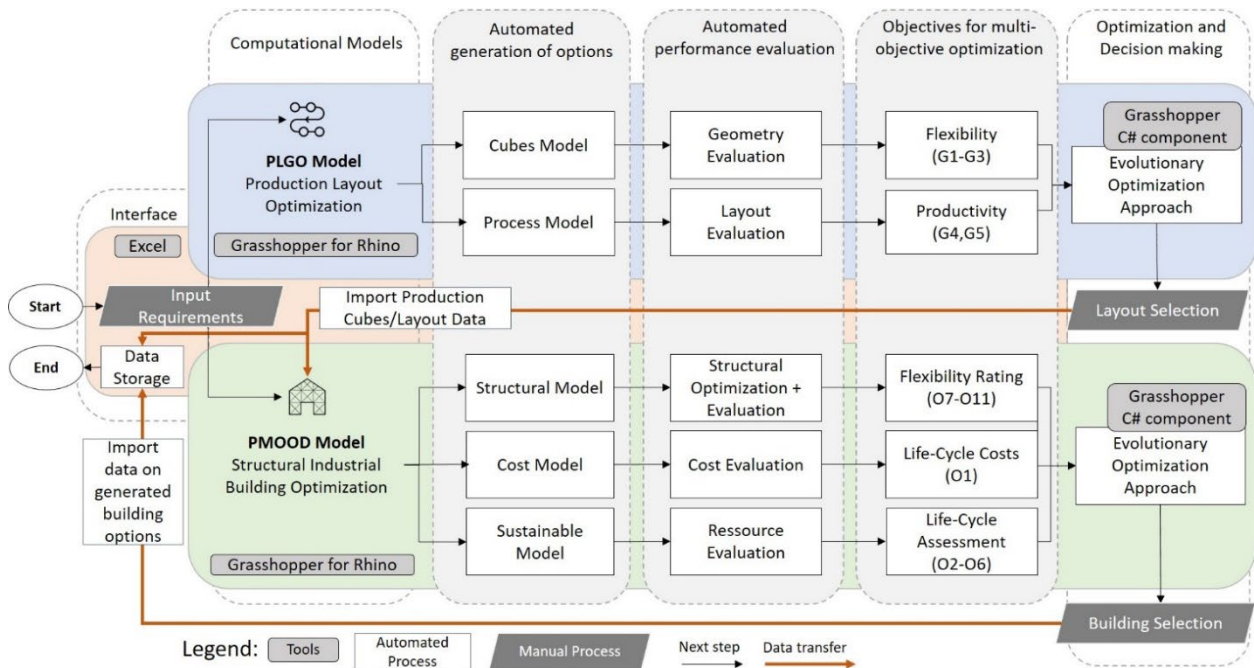


Figure 1: Framework and process for integrated parametric multi-objective optimization of production and industrial buildings

objectives and constraints of the PLGO model were presented in detail in Reisinger et al. (2022b).

The PMOOD model

The parametric script of the PMOOD model serves as structural analysis, performance assessment and multi-objective optimization tool, integrating a method to consider production layout scenarios. Figure 2 presents the parametric framework of the PMOOD model in Grasshopper.

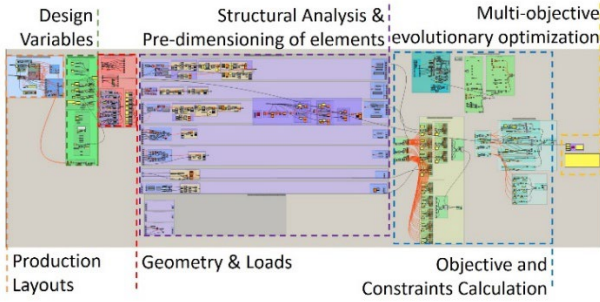


Figure 2: Framework of the PMOOD model for structural industrial building design optimization in Grasshopper.

The framework consists of the following six elements that in total comprise the PMOOD model:

- Integrating production layout scenarios:

The geometry and load requirements of the chosen production layouts from the PLGO model are integrated in the PMOOD model and serve as inner geometrical constraint for the building generation and as load case applied to the structural system.

- Design variables:

The design variables considered as parameters for the multi-objective optimization algorithm are the axis grid dimension and number of axis fields in primary and secondary direction, the inner hall height, the roof structure type in primary and secondary direction, the column type, the bracing type, structural material types and the load case types. A detailed presentation of the design space with a description of the variables for the parametric industrial building model can be found in Reisinger (2021).

- Geometry & loads generation:

The base geometry of the building is generated as a wireframe model, according to the definition of the axis grid. Simultaneously, loads such as snow, wind, live and production loads, are applied automatically.

- Structural analysis and element dimensioning:

The structural element types are generated based on the wireframe model and the structural type and material variables. After generation of the structural system and associated elements, the structural analysis is carried out by pre-dimensioning the structural elements, using Grasshopper components of Karamba3D.

- Objective and constraints calculation:

The objective and constraint calculation for performance assessment of the structural system in terms of LCC, LCA and flexibility is performed directly in the parametric modelling environment. Table 1 shows the implemented objectives and constraints for multi-objective

optimization. The PMOOD model optimizes the building structures according to one economic performance objective (O1), five environmental related objectives (O2 – O6) and five flexibility measuring objectives (O7 – O11). The used methodologies for the calculation of these objectives are based on ISO 15686-5 for O1 the LCC (ISO/TC59), on IBO (2018b) for the LCA related objectives (O2 – O5) and on IBO (2018a) for the recycling potential assessment O6. The flexibility objectives O7 to O10 are based on the calculation of the four flexibility metrics presented and mathematically described in Reisinger (2021). Objective O11 counts how many of the considered production layout scenarios can be accommodated in the generated building option. The goal of O11 is to maximize the number of layout scenarios that can be incorporated into the rectangular building boundary. A detailed description of the given constraints in Table 1 can be found in Reisinger (2021).

Table 1: Objectives and set of constraints for multi-objective optimization in the PMOOD model

O	Objectives [metric]	Calculation
O1	Life cycle costs [€]	(ISO/TC59)
O2	Global Warming Potential (GWP) [kgCO ₂ equ.]	(IBO, 2018b)
O3	Acidification Potential [kgSO ₂ equ.]	(IBO, 2018b)
O4	Primary Energy Intensity [MJ]	(IBO, 2018b)
O5	Primary Energy Non-Renew. [MJ]	(IBO, 2018b)
O6	Recycling Rate [Grade 1 – 5]	(IBO, 2018a)
O7	Retrofittability [kN/m ²]	(Reisinger, 2021)
O8	Expandability [m ²]	(Reisinger, 2021)
O9	Flexibility in space [m]	(Reisinger, 2021)
O10	Flexibility floor plan [m ²]	(Reisinger, 2021)
O11	Production scenarios [%]	Maximize number of layouts, fitting into the building
X	Constraints	Allowed values
X1	Structural stress utilization ≤ 1.0	[0,1]
X2	Building height \leq max. property height	[0,1]
X3	Structural displacement \leq allowable displacement	[0, x]
X4	Building dimension $>$ production layout boundary	[0,1]
X5	Building dimension $<$ property dimension	[0,1]
X6	Secondary axis grid $<$ span width of tertiary system (6 m)	[0,6]
X7	Stability of structural system	[true, false]

- Multi-objective evolutionary optimization:

The evolutionary algorithms for multi-objective optimization are written in C# and implemented in the parametric framework within a customized Grasshopper component. The grasshopper C# component contains the Pareto evolutionary algorithms of SPEA2, SPEA2+SDE and CTAEA. The parametric framework calculates for the

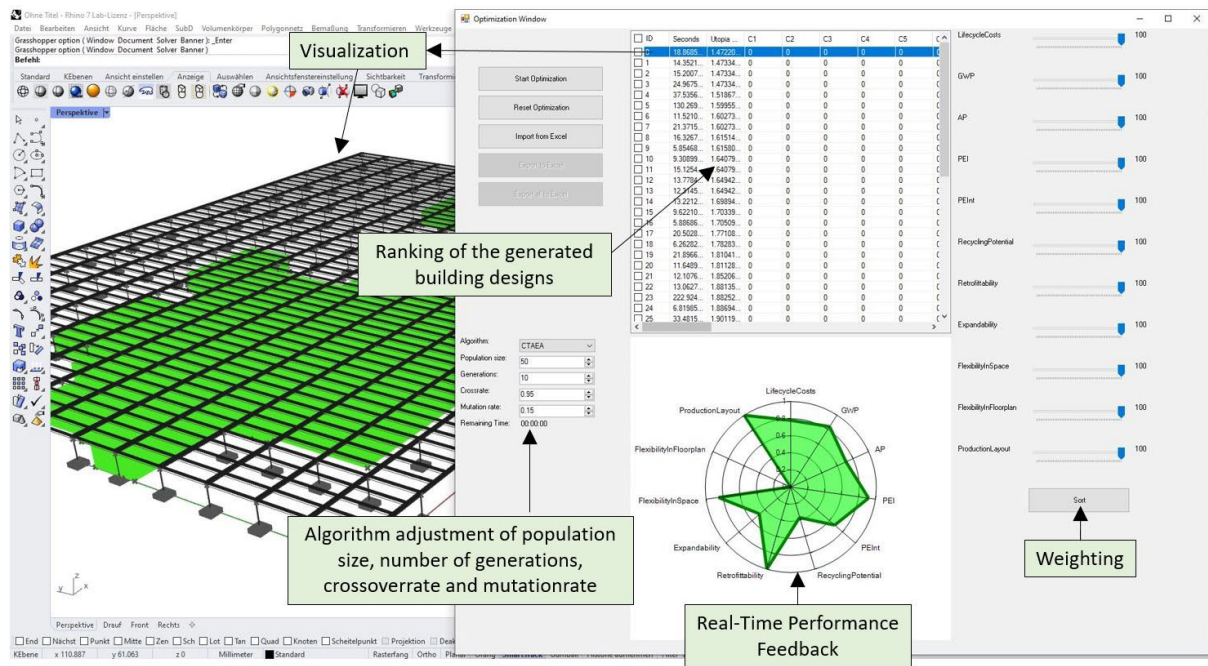


Figure 3: Developed multi-objective optimization window that shows ranking of the generated designs. Performance feedback of each selected option is provided in real time. The weighting can be applied individually for each objective on the right window side.

given set of variables the objective values and constraints. The optimization tool manipulates the framework's input parameters, lets the framework compute the objectives and constraints, and updates the population according to the chosen evolutionary algorithm. New inputs are calculated from the evolutionary algorithm and are fed back to the framework. Figure 3 presents the developed customized interface for multi-objective optimization in the PMOOD model. The user can choose which algorithm to use for optimization. For the evolutionary algorithm population size, number of generation, crossover rate and mutation rate can be directly adjusted in the optimization interface. The archive size is the same size as the population size. After optimization, the layouts are ranked per default by distance to the ideal point (Li et al., 2019). After optimization, users can sort the generated options using weights to facilitate design exploration.

Framework validation

The PMOOD framework is tested in the context of an interdisciplinary user study on a real hygiene production facility from Austria. It is validated if the framework can help diverse teams of students to efficiently explore the design space and find feasible and satisfying industrial building solutions in terms of design, economic, environmental and flexibility performance objectives.

User study

The empirical user study was conducted to test if the use of the PMOOD model with multi-objective optimization can provide building solutions with higher acceptance and satisfaction than manually investigated building options using the POD model with no optimization algorithm. The users were 36 master students from architecture and civil engineering at TU Wien. The students tested the framework in groups of two (18 groups), simulating an interdisciplinary design process and evaluating the design

exploration and decision-making support potential. The challenge was to find structural building solutions of the given task to maximize the value to both designers in the team regarding the LCC, the GWP and the flexibility performance. Thereby, the users needed to investigate and discuss the following design parameters: the layout selection, the configuration and materiality of the roof structure and the axis grid combination. Every design team was asked to conduct two separate tasks with a time availability of 45 minutes of each task. Thus, we encouraged the teams to simulate two design exploration processes, each time recording their five best-found designs. The two simulation tasks were the following:

- Using the POD model and finding satisfying building variants by manually manipulating the variables.
- Using the PMOOD model, investigating the building solutions provided by the algorithm and selecting the best performing solutions according to their design intend. Performing the optimization with the PMOOD model, the chosen population size for the test case was 50 with 20 generations.

To avoid the learning effect in the study, eight teams started with the POD model and the other eight teams started with the PMOOD model. After completing both tasks, the teams had to decide which of the generated designs they ultimately prefer, announcing if they choose a final building solution found with the POD or the PMOOD model.

Results

The results of the study showed that slightly more teams chose the manually generated building solution of the POD model as final result. Ten groups chose the manual variant of the POD model and eight groups found an

automated generated building option of the PMOOD model better for their needs, see Table 2.

Table 2: Results of the user study - selected options

Start	Chose final POD option	Chose final PMOOD option
Started with POD	4	5
Started with PMOOD	6	3
Total	10	8

The final chosen manual POD and automated PMOOD building variants have been compared regarding their objectives, see Table 3. In 14 cases, neither the POD option nor the PMOOD option was clearly better in terms of the trade-off performance results. The choice between the POD and PMOOD option would therefore be one of preference. Two groups had a PMOOD option that performed clearly better than the POD option and both groups selected the PMOOD option as their final result. In two other groups, the POD option performed clearly better than the PMOOD option. However, instead of choosing the POD option, one group chose the PMOOD option. Possibly this indicates other preferences that could not be covered by the objectives, i.e. design.

Table 3: Selection of options concerning performance results

Performance Results	Chose POD option	Chose PMOOD option	Total
Comparable results	9	5	14
POD better	1	1	2
PMOOD better	0	2	2
Total	10	8	18

Major differences between the investigated designs with the POD and PMOOD model could be found in terms of axis grid, materiality and roof structure types, see Figure 4 and 5. The design space of the PMOOD model considers the roof structure types timber girders (TG), timber frameworks (TF), steel girders (SG), steel frameworks (SF) and T-precast concrete beams (C). Within the PMOOD test, the design teams considered 24 times a concrete construction in primary and secondary direction, 9 times a concrete beam/timber girder combination and 9 times a concrete beam/steel framework construction. When working with the POD model, the groups considered 14 times a timber girder construction in primary and secondary direction, 10 times a timber framework/timber girder construction and 9 times a steel framework construction or concrete beam/timber girder combination. The combinations timber girder with concrete beam, steel girder with concrete beam, and steel framework with concrete beam was only chosen when working with the PMOOD model, but would not have been considered by the designers in manual alternative generation with the POD model. The one-sample chi-square test is used to assess statistical significance in distribution of preference answers. While the POD model was slightly more preferred than the PMOOD (10 vs. 8 votes), the results of chi-square analysis suggest that this

difference was not significant ($\chi^2 = 0.22$, $p = 0.64$). Finally, our hypothesis, that the PMOOD model is preferred over the POD model was not supported.

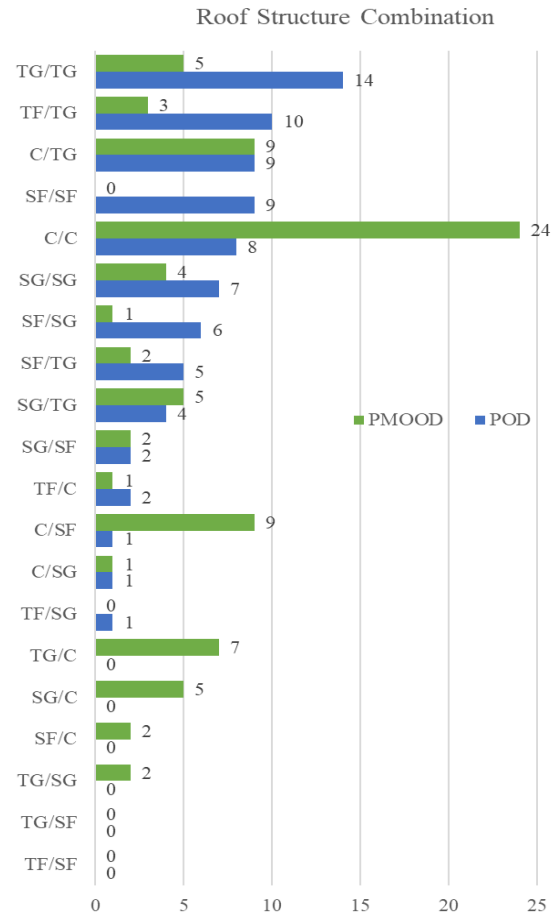


Figure 4: Structural combinations selected and investigated by the design teams using the POD and PMOOD models. The combinations are indicated in the following form: primary structure type / secondary structure type.

Discussion and conclusion

The presented research concerned the implementation of a multi-objective optimization algorithm into a parametric framework for integrated industrial building design (PMOOD model), capable of meeting spatial requirements from production processes on building scales with increased attention to maximizing flexibility and minimizing carbon emissions and costs that are embodied in the materials of the load-bearing structure. A method is provided to enable integration of production and structural building design to achieve seamless operation and interoperability without having to use multiple software packages. Providing a customized optimization interface in Grasshopper makes the parametric interface more user-friendly and ensures that the users require no coding skills. The framework and algorithm were tested in an interdisciplinary user study on a pilot project of a hygiene production plant. It was evaluated whether the use of the PMOOD model with multi-objective evolutionary optimization can lead to building solutions with higher acceptance and satisfaction than manually created building variants using the POD model with no automated design exploration. Results

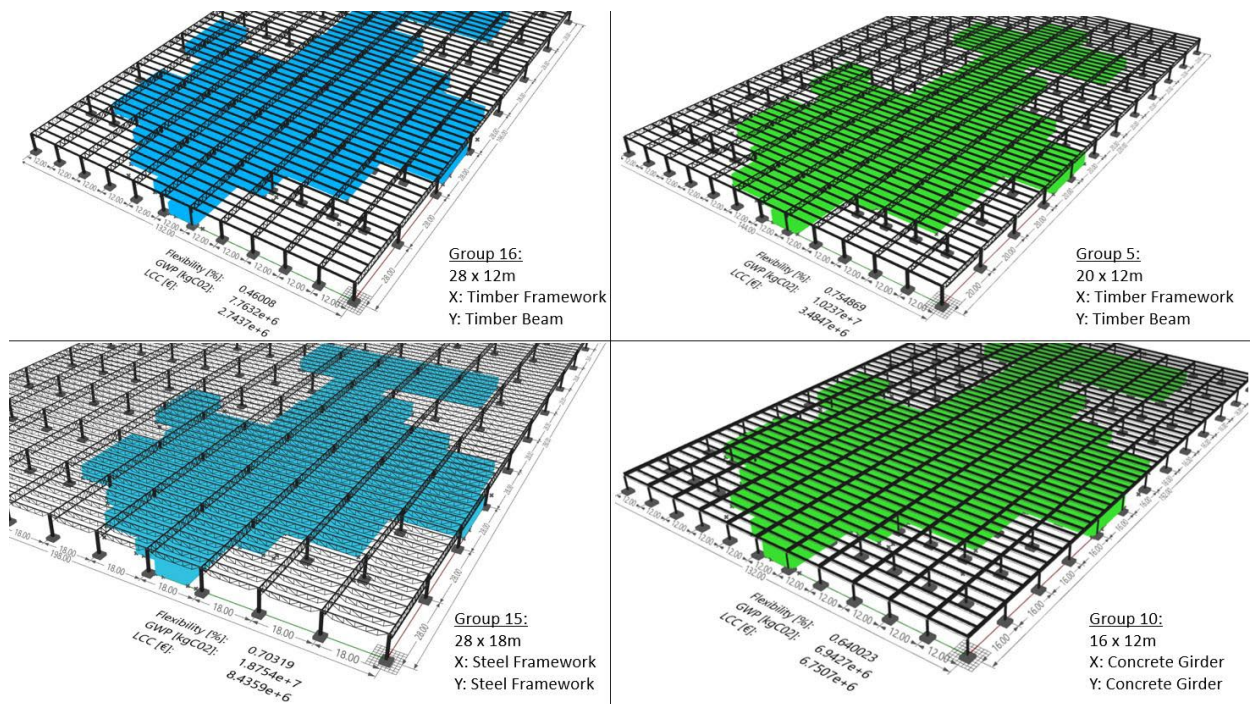


Figure 5: Examples of generated building options within the user study: Groups 15 and 16 chose the POD option (left column with blue production layouts) and the groups 5 and 10 chose the PMOOD option (right column with green production layouts).

reveal that the PMOOD framework can be useful in providing interdisciplinary stakeholders with a better understanding of the implications of their design decisions. Considering the final choices of investigated building options and related performance of objectives, we did not find a statistically significant difference that the PMOOD model is preferred over the POD model. In this regard, the PMOOD model could potentially replace manual creation and reduce time for design generation and exploration, but it would not provide "better" solutions. It has been noticed that the five best rated automated generated PMOOD options are roof support structures with concrete beams in primary and secondary direction. Thus, the design teams very often chose concrete structures in the PMOOD selection, which they would not have investigated in manual design search. This indicates that material combinations are a critical factor, which are not yet considered in the algorithm. In performing the PMOOD optimization, a population size of 50 with 20 generations was chosen for the test case, resulting in 1000 building options. However, given the size of the design space, more than 13.000 combinations would have been possible. It cannot be guaranteed if the algorithm found the best options, affecting the outcome of the user study. This research focused on the development of the parametric framework and evolutionary algorithm. Existing LCC, recycling, and LCA data and methods were used, but their indicators and methods were not analyzed in depth in this study. Evaluation of data quality and variability in the environmental and economic outcomes will be explored in more detail in future research.

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